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Case Report ■

Computerized Extraction of Information on the Quality of Diabetes Care from Free Text in Electronic Patient Records of General Practitioners

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Abstract Objective: This study evaluated a computerized method for extracting numeric clinical measurements related to diabetes care from free text in electronic patient records (EPR) of general practitioners.

Design and Measurements: Accuracy of this number-oriented approach was compared to manual chart abstraction. Audits measured performance in clinical practice for two commonly used electronic record systems.

Results: Numeric measurements embedded within free text of the EPRs constituted 80% of relevant measurements. For 11 of 13 clinical measurements, the study extraction method was 94%–100% sensitive with a positive predictive value (PPV) of 85%–100%. Post-processing increased sensitivity several points and improved PPV to 100%. Application in clinical practice involved processing times averaging 7.8 minutes per 100 patients to extract all relevant data.

Conclusion: The study method converted numeric clinical information to structured data with high accuracy, and enabled research and quality of care assessments for practices lacking structured data entry.

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Introduction

Routine entry of clinical information in electronic patient records (“registration”) comprises an important data source for healthcare research and quality improvement. The 1990s saw creation of several European general practice registration networks.^{1–7} Most such networks collect selected information from structured tables embedded in the electronic patient record (EPR) systems—for example, patients’ prescribing records, diagnostic codes, and demographic information.

Despite recognized potential and widespread pleas to register more structured clinical data, relevant, important clinical information remained scattered throughout different segments of the EPR. Much of that information, of great

potential interest for research and quality improvement, only resided in the free text of patient records.^{8–10} Physicians embed key information in free text instead of EPR structured tables due to time constraints during patient care, uncertainty about using codes, classification limitations, and inexperience and difficulties with the computer systems.^{1,2,8,11}

Many approaches to information retrieval exist.¹² In particular, Natural Language Processing (NLP) shows promising results for extracting and structuring clinical information from unstructured, “free text” medical records.^{13,14} For example, NLP applications have classified medical problems lists,^{15,16} extracted disease-related concepts from narrative reports,^{17,18} and combined data from multiple discharge

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summaries.¹⁹ NLP, however, has limitations making it less suitable for handling dense, telegraphic, ungrammatical clinical data that lack fixed structure and recognizable text formats. Furthermore, misspellings, personal idiosyncrasies, and transient local abbreviations make the words used to identify numeric data in free text highly variable and ambiguous. Thus, it is better to develop an extraction approach triggered by numeric values, per se, rather than their labels.

Case Description

Often, manual record abstraction occurs during the quality assessment of diabetes care.^{20–22} Requisite clinical information usually includes measurements of blood pressure, weight, height, and laboratory results.^{23–25} While administrative or centralized clinical databases contain some of these data, incomplete data registration in such systems often necessitates additional patient record review.²⁶ A need exists for automated capture of these data from EPRs. Such a method must be applicable across multiple sites lacking uniform data registration procedures.

Most general practices in The Netherlands use one of seven vendors' major electronic patient record systems. The EPR information collected by general practitioners (GPs) can be stored either as structured tables or written free text fields. Text fields contain various notes entered by the GP or the GP's assistants, including summaries of reports from outside sources. Sometimes clinicians embed electronically transmitted laboratory test results within free text fields, instead of the intended structured tables.

This study developed and evaluated a computerized extraction method to convert numeric clinical information stored anywhere in an EPR into structured data. There were no prerequisites for how and where the information was registered during general practice. The method addresses the following issues: 1) accuracy of data extraction for numeric clinical measurements relevant to diabetes care; 2) performance of the extraction method during clinical practice, and post-processing actions needed to optimize accuracy.

Methods

The study identified 13 numeric clinical measurements considered relevant for evaluating the quality of diabetes care.^{23–25} These included measurements of systolic (SBP) and diastolic (DBP) blood pressure, weight, height, serum glucose (fasting, non-fasting, unspecified), glycosylated hemoglobin (HbA_{1c}), and several measures of serum cholesterol (total, TC; high-density lipoprotein, HDL-C; and, low-density lipoprotein, LDL-C), triglycerides, and serum creatinine.

Data Extraction Method

The computerized extraction method, triggered by numeric values in free text fields of the EPR, utilized nearby names and abbreviations used to label the measurement, including units and other specifications added to numeric values. A vocabulary of potential labels or specifications related to numeric values was generated by examining all unique words within two words from numbers embedded in text

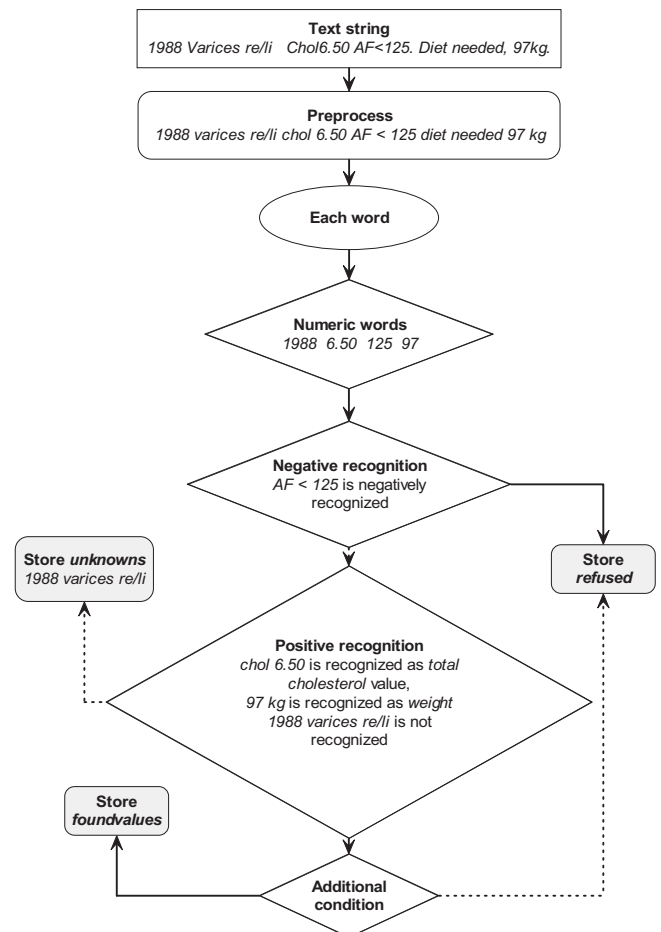


Figure 1. Flow of the data extraction method (continuous lines are positive actions, interrupted lines are negative actions), with example text string.

strings. Two authors independently reviewed this vocabulary and classified words as either belonging to a numeric measurement of interest or not. This vocabulary was used to select a text recognition algorithm that could correctly identify target words that varied in length, likelihood of different ways of spelling, and possible misinterpretation due to typing errors (see online-only Appendix, available at www.jamia.org). A character sequence algorithm was found to be most suitable for recognition of measurement labels, and therefore included in the data extraction method.

The data extraction method converted free text numeric measurement information into structured data (Figure 1) as follows: (a) text strings, preprocessed to split compound strings and standardize character use, were split into substrings representing individual words; (b) each substring was classified as either containing or not containing relevant numeric values. Negative recognition (identification of irrelevant numerical values) involved evaluation of the four words neighboring a numeric substring, through comparison with a list of “negative definitions” for numeric values not of interest. Similarly, positive recognition involved comparison of neighboring words to the definitions made for each clinical measurement of interest. These comparisons included multiple definitions, so that, for example, “blood

Table 1 ■ Accuracy of Data Extraction of 60 EPRs from 6 GP Practices

Clinical Measurement	N	Sensitivity		Positive Predictive Value	
		BP	AP	BP	AP
Diastolic Blood Pressure	165	93.9	93.9	100.0	100.0
Systolic Blood Pressure	166	95.2	95.2	96.9	100.0
Weight	72	100.0	100.0	100.0	100.0
Height	16	100.0	100.0	19.3	100.0
Glucose fasting	64	84.4	89.1	91.5	100.0
Glucose non-fasting	89	94.4	97.8	100.0	100.0
Glucose unspecified	145	66.2	68.7	85.7	100.0
HbA1c	154	98.7	100.0	99.3	100.0
Total cholesterol	57	98.2	98.2	100.0	100.0
HDL cholesterol	42	95.2	95.2	51.3	100.0
LDL cholesterol	38	94.7	94.9	97.3	100.0
Triglycerides	38	100.0	100.0	100.0	100.0
Creatinine	55	96.4	100.0	100.0	100.0

N = number of observations present in gold standard; sensitivity and positive predictive value before (BP) and after (AP) post-processing; HbA1c = glycosylated hemoglobin; HDL = high-density lipoprotein cholesterol; LDL = low-density lipoprotein cholesterol.

sugar” and “glucose” will both be recognized to represent the same clinical measurement. Unrecognized numeric values are stored together with their context words in a separate “unknowns” table which is monitored during the post-processing procedure. Authors incorporated this data extraction method into a software application that accesses two of the most commonly used EPR systems operating in general practice.

Post-Processing Procedures

Most data of interest were originally manually entered into an EPR system by clinical personnel. Data entry errors were possible, and errors in numerical text identification might occur. A stepwise, semi-automated post-processing procedure was developed to identify and correct potential errors in extracted data, including checking for numeric values outside specified ranges, identifying unexpected peaks in clinical measurement time-series, and locating specific information in the “unknowns” table. Identified potential errors were visually reviewed by a trained registration worker, who could correct a numeric value or its variable allocation, delete erroneous data, or add missed data. All such actions were logged, together with reasons for modifications. Reasons were classified into three categories: (1) data entry errors in the GP practice (e.g., typing errors), (2) problems introduced by the automated data extraction system (e.g., false positives, cutoff or goal values instead of actual clinical measurements, dates instead of values), and (3) general data problems occurring in electronic databases (e.g., unit conversions or bogus values introduced by EPR system conversions).

Evaluation

Extraction method accuracy was assessed by comparison with a gold standard dataset of manually abstracted EPRs. Sixty randomly selected complete patient records from six GPs served as the gold standard. A single reviewer identified all values for any of the 13 selected measurements reported during one year. Verification involved double coding of 30 gold standard EPRs by an independent general practitioner. For these 30 records, agreement was excellent between both reviewers ($\kappa = 0.98$). Sensitivity was measured as the proportion of correct (gold standard) measurements found

with the automated data extraction method; and positive predictive value was determined as the proportion of gold standard (correct) measurements compared to the total number of extracted measurements—calculated before and after post-processing.

The evaluation in clinical practice utilized the data extraction software on two EPR systems in ten GP practices. Data were extracted for all 767 patients previously identified with type 2 diabetes in these practices. The two EPR systems (*Promedico* and *MicroHIS*) comprised two-thirds of the market share in the study region. The GP practices for this test were different from those contributing to the gold standard. During the evaluation, the data extraction software logged the time it required for data retrieval and interpretation. Additional effort to perform post-processing procedures was timed by activity logging in the central database maintenance software.

The regional Scientific Advisory Group of the General Practitioners Association approved the anonymous data collection procedure for this project.

Example

For the first dataset of 60 EPRs, 80% of the observations for the 13 selected measurements occurred only in free text segments of the EPRs; for 5 out of the 13 selected measurements this was above 90%. Between 3 and 12 unique labels were associated with each selected clinical measurement. During clinical practice evaluations, median rates of observations available only in free text fields ranged from 74% to 99%. Rates of structured registration varied considerably among GP practices. The number of unique labels within and between GP practices varied widely. For example, we found a total of 39 unique labels for “unspecified glucose value” in the GP practices, with each individual GP practice using 5 to 21 of them.

The data extraction software sensitivity exceeded 84% (compared to the gold standard) for all clinical measurements of interest except unspecified glucose. False positive results generated by the method caused low positive predictive values for height and HDL-cholesterol, but good PPVs for other measurements (Table 1). Applying the post-processing

Table 2 ■ Numbers of Valid Data Extractions and Corrective Actions Needed During Post-processing in the Field Test (10 GP practices), Standardized to a Population of 100 Patients per Practice

	Min	Max	Mean (SD)
Valid extractions (n)	2,216	14,090	9,156 (4,362)
Corrective actions (n)	172	1,894	815 (504)
% Valid extractions	72.4	97.4	89.8 (8.1)
Ratio Valid/Actions	2.6	37.1	15.3 (11.3)

procedure improved the sensitivity for six of the clinical measurements, and increased the PPV to 100% for all measurements (Table 1).

Time to conduct data retrieval from EPR systems operating in actual practice ranged from 1.8 to 8.2 minutes per 100 patients. For the data interpretation, the software required 0.3–7.7 minutes per 100 patients. Total data extraction (retrieval plus interpretation), on average took 7.8 (s.d. 4.0) minutes per 100 patients. Effort to perform post-processing procedures varied between 42 and 184 minutes per 100 patients (mean 119). The total number of numeric measurements of interest extracted per practice ranged from 2,216 to 14,090 per 100 patients. The proportion of extracted data considered valid before post-processing was 72%–97% (Table 2). Deletion was the most common corrective action, followed by addition of data that had not been recognized by the computerized data extraction method (Table 3). An average of 87% (range per practice 56%–99%) of deletions removed erroneously identified values. For example, numeric values with “t” sometimes labeled other things than the wanted blood pressure (“tension”) results. Remaining deletions removed either incorrect values due to general database problems, or addressed data entry errors, e.g., tagging urine creatinine values as serum creatinines, or typing errors. Most often (49%), value modifications addressed unit conversions for height (m vs. cm). Overall, the proportion of corrections required to address data entry errors by GPs was 11%, ranging between 2% and 41%; the proportion due to general database errors was 14% (Table 3).

Discussion

While the study EPRs could store data in structured tables, in practice, 80% of the numeric data for 13 diabetes-related clinical measurements occurred in free text segments of EPRs. The study data extraction method performed with a generally high sensitivity and positive predictive value, despite large variations in relevant-data-identifying labels both within and between practices. Results depended upon

combination of a highly customizable text recognition algorithm, a number-oriented extraction method, and a semi-automated post-processing procedure.

Study data extraction procedures demonstrated feasibility of improved data collection without additional data registration or verification work for participating clinicians. Most of the study workload occurred at the central level during post-processing, with a maximum of 1.8 minutes needed per patient. Post-processing helps to maximize rates of correct observations extracted,²⁷ and was considered necessary to eliminate GP data entry errors. Information obtained during post-processing can improve text recognition definitions, increase accuracy of the extraction methods, and decrease workload of post-processing.

The alternative to the approach used in this study is to manually collect and review patient records for data extraction. In a Dutch project focusing on diabetes care in primary care,²⁸ manually collecting relevant clinical data from patient records required at least ten minutes per patient.

Recently, a JAMIA study reported abstracting blood pressure measurements from text notes using a label-oriented approach with similar accuracy to the current study.²⁹ Such label-oriented approaches apply lists of regular expressions for extraction, and are only feasible in situations where labeling styles are invariable. Otherwise, label-oriented approaches can result in poorer accuracy than number-oriented approaches.

Some researchers view structured data registration and standardization as the ultimate solution to achieve full benefits from EPRs. However, a combination of free text and structured data registration must exist for adequate patient record-keeping.³⁰ All record systems must accommodate clinicians' workflows, and efforts for correct EPR use should be minimal.³¹ For most GPs, the quickest way to record data involves generating a few lines of text.^{10,32} When computer-based decision support systems require onerous efforts to achieve better data registration during routine practice, rates of system usage are often suboptimal.^{33–35} Inflexible data collection forms with predefined items may fit the workflow of a specialized environment, but in general practice anticipation of data registration is difficult.

Limitations and Generalizability

This study focused on the extraction of numeric clinical measurements relevant for diabetes care. By including a wide range of measurements coming from physical examination and laboratory results, the study demonstrated applicability for collecting data from EPRs involving numeric

Table 3 ■ Type and Underlying Reasons for Corrective Actions Needed During Post-processing in the Field Test (10 GP practices), Standardized to a Population of 100 Patients per Practice

	General Database Error Mean (SD)	Data Entry Error GP Mean (SD)	Extraction Error Mean (SD)	Total Mean (SD)
Deleted data (n)	45.1 (110.5)	28.1 (27.8)	455.1 (406.3)	528.3 (500.6)
Modified value (n)	71.9 (63.2)	32.7 (36.7)	20.8 (25.0)	125.3 (96.7)
Modified variable (n)	0.0 (0.0)	0.0 (0.0)	20.6 (22.2)	20.6 (22.2)
Added data (n)	0.0 (0.0)	21.9 (43.6)	118.9 (123.4)	140.8 (128.2)
% Corrective actions	13.6 (10.8)	11.4 (11.9)	75.0 (16.6)	

values. The study applied data extraction software to two of the seven EPR systems used in Dutch general practice, but could easily be applied in other settings. No differences in sensitivity of data collection occurred between the two EPR systems. The authors have no reason to expect that this method will perform differently within other EPR systems. Conversely, a higher (adequate) use of structured tables for clinical data entry would improve upon observed PPVs before post-processing.

Conclusions

The study extraction method identifies and converts to structured data selected numeric clinical information stored anywhere within tested EPR systems. This method offers considerable advantages over existing methods that rely on structured data registration or manual data extraction. The method, through its generality, appears to hold potential value for conducting health services research and quality of care assessments in general practice.

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